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FOSTERING SCIENCE IDENTITY IN SECONDARY SCHOOL STUDENTS THROUGH IOT-INTEGRATED EXPERIENTIAL STEM EDUCATION IN AGRICULTURE

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Abstract. *Science identity, comprising core components such as Science Capital, Epistemic Beliefs, and Environmental Agency, has been identified by PISA 2025 as a key indicator of 21st-century citizen competency. However, contemporary STEM education often lacks effective pedagogical strategies to foster these multifaceted dimensions of science identity in authentic contexts. This study evaluated the impact of an experiential STEM model integrated with Internet of Things (IoT) technology on the development of science identity among secondary school students in Vietnam. Using an explanatory sequential mixed-methods design, a quasi-experiment was conducted with 102 eleventh-grade students. The experimental group participated in a 10-week IoT-based agricultural project, while the control group received conventional instruction. Quantitative data were collected using a validated science identity scale and analysed via ANCOVA, supplemented by qualitative insights from student learning journals and interviews. Findings demonstrated that the STEM-IoT model significantly enhanced overall science identity with a large effect size (Cohen's d = 0.82), with environmental agency showing the strongest gains (d = 0.57). Qualitative analysis revealed that engagement with complex, real-world IoT data generated "epistemic friction," prompting a shift from simplistic views of scientific knowledge as absolute towards critical inquiry and bolstering students' perceived agency. This study provides a validated measurement instrument and evidence that technology-integrated, contextually grounded STEM pedagogy can effectively advance the competencies emphasized in the PISA 2025 framework.*

Keywords: *STEM, IoT, science identity, PISA 2025, epistemic friction*

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Introduction

Research Problem

Science education in Vietnam, as elsewhere, struggles to bridge the gap between classroom knowledge and solving real-world problems. The 2018 General Education Program addresses this by making STEM education a core strategy for integration (Le & Pham, 2025; Ministry of Education and Training, 2020). This shift reflects a wider global trend where curricula now prioritise developing core competencies and modern citizenship over simply transmitting facts (Garcés et al., 2025; González-Pérez et al., 2022; White et al., 2023). For teachers in Vietnam, however, a key hurdle remains: moving beyond standard lab exercises to design STEM activities that engage students with urgent local socio-ecological issues, such as water pollution or sustainable farming, within the constraints of typical public-school facilities.

International assessments are also changing. The PISA 2025 Science Framework, for instance, now treats Science Identity (SI) as a primary goal (White et al., 2023). Unlike technical skill, SI involves how students see themselves, the value they place on science, and their sense of belonging in scientific communities (Ding, 2025; OECD, 2023). Research consistently shows that SI predicts long-term STEM interest and career choices more reliably than grades alone (Archer et al., 2015; Le & Pham, 2023). Thus, if STEM education in Vietnam focuses only on skills and fails to help students internalise an identity as a science person, it is unlikely to build a sustainable, high-quality workforce for the nation's future development.

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Research Focus

A significant gap remains in current STEM education. Although research has firmly established that STEM interventions improve content knowledge, studies now indicate these conventional methods often fail to change students' epistemic beliefs or foster a strong sense of environmental agency (Nong et al., 2022). This shortcoming stems from the use of idealised, controlled learning environments that shield students from the uncertainty and complexity of real-world problems (Xu et al., 2025; Kerwer & Rosman, 2018).

To address this gap, an integrated framework is proposed, based on experiential STEM education using IoT technology in a smart agriculture context. This approach goes beyond simply using new tools; it employs IoT as a deliberate teaching method to create "epistemic friction." For instance, high school students in Vietnam might use soil sensors that yield unpredictable, real-time data, forcing them to grapple with the messy variability of actual scientific work (Allchin, 2012). The central hypothesis is that by navigating this uncertainty while solving practical problems, like optimising water use for lettuce in a school garden. Students can develop the three core components of science identity outlined in PISA 2025: Science Capital (SC), Epistemic Beliefs (EB), and Environmental Agency (EA) (OECD, 2023).

Theoretical Background

The Measurement Structure of SI in the PISA 2025 Framework

This study operationalises Science Identity (SI) using the PISA 2025 framework. The framework conceptualises SI not as a single trait but as three dynamically interacting components, capturing both the personal and social dimensions of a student's relationship with science (OECD, 2023).

The first component, Epistemic Beliefs (EB), assesses how students understand the nature of science, going beyond mere content knowledge. Following Hofer (2004), it examines whether students value evidence over opinion, understand science as a process of critique and consensus, and accept that scientific claims are inherently tentative. Table 1 details these dimensions.

The second component, Science Capital (SC), is grounded in sociological theory (Archer et al., 2015). It accounts for the unevenly distributed resources that shape engagement. In the Vietnamese context, relevant resources include not only academic knowledge but also attitudes toward science, participation in local science clubs or competitions, and social connections. For example, having a family member who works in a technical field can support a science-related identity (see Table 2).

The third component, Environmental Agency (EA), is the framework's future-oriented element. PISA 2025 argues that in an era of socio-ecological crises, scientific literacy must include the conviction that one can act. EA therefore measures a student's belief in their own efficacy, their hope for sustainable solutions, and their ability to think in systems. These competencies are critical for translating knowledge into tangible action within local communities (OECD, 2023; Table 3).

Table 1
Dimensions of EB

Core Dimension	Conceptual Descriptors
Commitment to Evidence	Regarding evidence as the sole basis for explaining the physical world and forming beliefs (OECD, 2023).
Appreciation of Critique and Consensus	Valuing the peer-review process and recognising scientific consensus as a reliable mechanism for knowledge validation (OECD, 2023; Schiefer et al., 2022).
Tentativeness and Uncertainty	Understanding that scientific knowledge evolves and that uncertainty is an inherent feature, requiring continuous assessment of risk and probability (Bråten et al., 2011; Deta et al., 2025).

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Table 2
Dimensions of SC

Core Dimension	Conceptual Descriptors
Science-related Knowledge	The ability to mobilise both content and procedural knowledge (DeWitt et al., 2016; OECD, 2023).
Attitudes and Dispositions	A sense of belonging, perceiving the relevance of science to everyday life, and intrinsic interest (Archer et al., 2015).
Participation in Science	Engagement in out-of-school STEM/science activities, reflecting personal interest (Moote et al., 2020; OECD, 2023).
Science-related Social Capital	Support from family, peers, or networks of individuals working in science/STEM fields (Moote et al., 2020).

Table 3
Dimensions of EA

Core Dimension	Conceptual Descriptors
Self-efficacy	Belief in one's personal capability to perform science-related or environmental tasks (Bandura, 2001).
Hope	The perception that a pathway toward a sustainable future exists, particularly through collective efficacy (OECD, 2023).
Systems Thinking	The capacity to recognise complex interactions between variables within socio-ecological systems is essential for sustainable decision-making (Meadows, 2008).

The IoT-Integrated Experiential STEM Pedagogical Model

This study proposes an experiential STEM education model to translate the Science Identity framework into classroom practice. The model integrates IoT technology within a smart agriculture context, designed as an intervention to holistically develop students' Science Identity (OECD, 2023). It shifts learning from treating knowledge as a static object to using it as a tool for action, emphasising how students can solve complex, ill-defined problems in local settings (Chin & Osborne, 2010; Kolb, 2015).

Structurally, the model synthesises Kolb's Experiential Learning Cycle with the Engineering Design Process to create a cyclical, solution-oriented approach. It was implemented through five phases on the theme "IoT Applications in Agriculture," such as monitoring variables like temperature and soil moisture for a specific crop common in the local region, like lettuce or morning glory.

Phase 1: Problem identification and field survey. Students begin with visits to local farms or family gardens. The goal is to identify real challenges, such as water waste from manual irrigation or crop loss due to temperature extremes, establishing a direct socio-scientific relevance for the project (Archer et al., 2015; Zeidler & Kahn, 2014).

Phase 2: Research and ideation. Students research electronics, sensors, and control principles. They use this academic knowledge to conceptualise and sketch preliminary designs for an automated IoT solution, moving from theory to application (ElSayary, 2021).

Phase 3: Design and fabrication. Here, students build. They assemble hardware, write code, and create working prototypes. This hands-on engineering work actively builds individual Science Capital through practical skill acquisition.

Phase 4: Empirical testing and data acquisition. Students deploy their prototypes in real conditions. The unpredictable, often messy sensor data they collect forces them to confront uncertainty, a process that challenges and refines their Epistemic Beliefs about how science works (Allchin, 2012).

Phase 5: Reflection and iterative refinement. Students analyse their data, evaluate system performance on metrics like precision, and refine their designs. This iterative, trial and error process strengthens self-efficacy and systems thinking, directly contributing to the development of their Environmental Agency (Bandura, 2001).

The organic linkage between the five phases presented above is not merely an order of execution but reflects an intentional pedagogical design: they constitute an integrated learning ecosystem where the output and experience of one phase become the essential input and driving force for the next. In this study, it was observed

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that by integrating hardware assembly with data analysis, students were able to a spiral progression in students' scientific cognition and identity. The core dynamic driving this complex progression can be conceptualised as Epistemic Friction.

Theoretically, this concept is adopted and adapted from Medina (2013), who views it as the constructive tension that arises when one's current belief system is confronted by alien, difficult-to-assimilate evidence. Within the STEM education context of this study, it is specified as a deliberately designed learning situation: the state of cognitive impasse and challenge that emerges when students must confront, interpret, and make decisions based on the raw, noisy, and imperfect data stream from IoT sensors in a real-world environment. Rather than an obstacle to eliminate, the discrepancy between expectations and real-world data compels students to think more deeply about the nature of knowledge. Students' initial confusion or scepticism upon encountering erratic sensor data signals a productive disruption. Their neat, theoretical models are colliding with messy reality. It is through the collective work of parsing this noisy data, debating its meaning, testing interpretations, and redesigning their systems that students' SI develops in an integrated way. This struggle directly activates and connects the growth of its three core components (SC, EB, and EA).

The development of SI within this model emerges from a dynamic interplay between the pedagogical phases and the core SI constructs. The process begins by anchoring abstract knowledge in local reality. The initial field exploration (Phase 1) serves a critical function beyond simple context-setting; it re-frames physics and technology as relevant tools for engaging with the students' own community. This act of localisation transforms academic concepts into applicable knowledge, thereby activating and valuing students' prior social understanding and relationships, a foundational step in building SC.

This foundation of relevance is then built upon through hands-on creation (Phases 2 & 3). The act of designing and fabricating a functional IoT system does more than develop technical skills. It embeds students within an authentic community of practice. By grappling with real design challenges, interacting with technical concepts, and producing a tangible artefact, students begin to see themselves as competent participants in a technical world. They are not just learning about engineering; they are doing engineering, which actively constructs their identity and belonging in this field, a direct contribution to their SC (Archer et al., 2015).

The cognitive core of the transformation occurs during confrontation with authentic data (Phase 4). Here, the IoT system reveals its role not as a passive tool, but as an active epistemic partner. It generates complex, often unpredictable data that directly challenges students' initial assumptions and idealised models. This noisy reality creates a necessary friction. To progress, students must engage in critical evaluation, distinguish signal from noise, and tolerate the uncertainty inherent in real-world evidence. This struggle is pivotal for evolving EB, moving students from a perspective of seeking fixed truths toward appreciating science as an evidence-based, iterative process of justification (Hofer & Pintrich, 1997).

Importantly, this process is not linear but highly iterative and self-reinforcing. The experience of success and the resulting sense of agency (EA) do not mark an endpoint. Instead, they initiate a positive feedback loop: proven competence strengthens students' interest and self-confidence, thereby enriching their SC. Simultaneously, navigating a complex, open-ended process validates its worth, leading to more sophisticated EB about how scientific knowledge is built. This enriched SC and refined EB, in turn, build the confidence and conceptual foundation needed to attempt even more complex and autonomous actions in the future, further strengthening EA. This dynamic creates an upward developmental spiral. Within this spiral, Epistemic Friction serves a dual function. It is the necessary resistance created by challenging, noisy data. This resistance disrupts simplistic thinking. Yet, by grappling with and overcoming this friction, students gain the traction needed to advance. It prevents their understanding from merely "spinning in place" and propels the sustained development of their Science Identity (Leung et al., 2025). This framework, elucidating the interdependent relationship between SC, EB, EA and the catalytic role of Epistemic Friction, will guide the analysis of both quantitative and qualitative results in the following section.

Research Aim and Research Questions

Grounded in the aforementioned theoretical underpinnings, this study aimed to develop a validated psychometric instrument and evaluate the empirical impact of the IoT-integrated STEM model on the trajectory of SI development among Vietnamese secondary school students. To achieve this aim, the research addressed the following two Research Questions (RQs):

RQ1: Is the tri-dimensional Science Identity scale (measuring SC, EB, and EA) a valid and reliable instrument for use with Vietnamese secondary school students?

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RQ2: What is the differential impact of the IoT-integrated experiential STEM model on the development of students' Science Identity, with a particular focus on Environmental Agency, in comparison to conventional instructional methods?

Research Methodology

General Background

This study used an explanatory sequential mixed methods design. The primary quantitative phase assessed the intervention's efficacy. A subsequent qualitative phase then helped explain the psychological mechanisms behind any quantitative changes.

For the quantitative stage, a quasi-experimental pretest-posttest design with a non-equivalent control group was implemented (Denny et al., 2023). This involved measuring the three Science Identity components in both an experimental and a control group at two time points: before and after the 10-week intervention. Table 4 outlines this structure.

Table 4
Schematic Representation of the Quasi-Experimental Research Design

Group	Pre-test	Treatment / Intervention (X)	Post-test
Experimental Group (nE)	O1	IoT-Integrated Experiential STEM Model	O2
Control Group (nC)	O3	Conventional Teaching Methods	O4

The NECGD framework facilitates the effective mitigation of critical threats to the study's internal validity, including history, maturation, and testing effects, as these factors exert a simultaneous influence on both groups (Cook et al., 2002). Any statistically significant divergence in the observed change between the two groups, after controlling for extraneous variables, is subsequently attributed to the net effect of the intervention (X).

To analyse the quantitative data, this research employs Analysis of Covariance (ANCOVA). Within this statistical model, pre-test scores (O1, O3) serve as covariates to statistically adjust the post-test scores (O2, O4) of the experimental and control groups. This procedure fulfills two primary objectives: (1) Mitigating Selection Bias: It rectifies any pre-existing baseline discrepancies between the groups at the pre-test stage, ensuring a more equitable comparison; (2) Augmenting Statistical Power: By accounting for the variance in the dependent variable attributable to the covariate, ANCOVA reduces residual error variance, thereby enhancing the model's sensitivity in detecting the true effect of the intervention.

Sample

The study involved 102 students in Grade 11 at Ong Ich Khiem Secondary School in Da Nang, all of whom were enrolled in the Physics elective module on electronics. The intervention took place in Dieu Phong Hamlet (Hoa Vang District), a rural area where small-scale farmers face practical challenges related to irrigation and protecting crops from temperature extremes.

Selecting a single, specific site with this convenience sample was a methodological choice to maximise ecological validity for the IoT agricultural intervention (Century et al., 2010). Although this limits broad statistical generalisation, a post hoc power analysis confirmed the sample size ($N = 102$) was sufficient to detect large effect sizes (Cohen's $d > 0.80$), which are common in intensive hands-on interventions (Faul et al., 2007).

A non-equivalent control group design used intact classes. Two classes with similar profiles were assigned as the Experimental Group ($n_E = 53$) and Control Group ($n_C = 49$). This assignment ensured baseline homogeneity based on three metrics: prior Physics GPA, gender distribution, and initial Science Identity scores.

To maintain internal validity, student attrition was monitored and remained negligible. As Table 5 shows, preliminary analyses found no statistically significant differences between groups at baseline. The p-values for Physics GPA ($p = .86$), gender distribution ($p = .76$), and initial SI ($p = .52$) all exceeded the .05 threshold (Field, 2024).

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This baseline parity allows for greater confidence that post-intervention differences are attributable to the STEM model itself, rather than pre-existing biases, justifying the subsequent use of ANCOVA (Miller & Chapman, 2001).

Table 5

Demographic Characteristics and Baseline Equivalence of the Sample

Variable	Experimental Group (n_E = 53)	Control Group (n_C = 49)	Test Statistic	*df*	*p*
Physics GPA	7.79 ± 0.56	7.78 ± 0.34	t = 0.17	100	.86
Gender			χ^2=0.09	1	.76
Male	60.40% (32)	57.10% (28)			
Female	39.60% (21)	42.90% (21)			
Pretest SI	74.94 ± 2.33	74.64 ± 2.31	t = 0.65	100	.52

Note. N = 102. Physics GPA and Pretest SI (Science Identity) values are presented as $M \pm SD$. M = Mean; SD = Standard Deviation; χ^2 = Chi-square test; t = Independent samples t-test.

Instrumentation and Reliability

The primary instrument employed in this study is the SI Scale, conceptualised based on the PISA 2025 tri-dimensional framework. The scale utilises a 5-point Likert-type format, ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). To ensure rigorous content validation, the initial draft was subjected to a formal evaluation by a panel of 15 experts specialising in Science/STEM Education, PISA assessment frameworks, and psychometric measurement.

The expert panel scrutinised each item based on two primary criteria: (1) Representativeness, ensuring the items accurately capture the theoretical constructs of the PISA 2025 framework; and (2) Linguistic Clarity and Contextual Alignment, ensuring the items are accessible to secondary school students and deeply situated within the STEM/IoT smart agriculture context. Item-level Content Validity Index (I-CVI) and Scale-level Content Validity Index (S-CVI) were calculated to quantify consensus. Following the initial round, items with an I-CVI below the 0.78 threshold (the minimum requirement for 15 experts) were revised based on qualitative feedback (Lynn, 1986). A subsequent round of review demonstrated high consensus, with the S-CVI/UA (Universal Agreement) exceeding 0.90 for each subscale (Polit & Beck, 2006), thereby confirming the instrument's robust content validity and contextual suitability.

Internal consistency was evaluated using Cronbach's Alpha coefficients. Analysis of the formal dataset (N = 385) revealed excellent reliability across all three subscales, substantially exceeding the recommended threshold of $\alpha > 0.7$: EB (α = .89); SC (α = .89); và EA (α = .90). Furthermore, all Corrected Item-Total Correlations were above 0.3, indicating that each item contributed effectively to the overall construct (Hair et al., 2009).

Exploratory Factor Analysis (EFA) was conducted to verify the underlying factor structure. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.93, and Bartlett's Test of Sphericity yielded significant results (χ^2; p < .001), confirming the data's suitability for factor analysis (Lorenzo-Seva, 2003). Using the Eigenvalue > 1 criterion, three distinct factors were extracted, accounting for 58.34% of the total variance explained. A Promax rotation matrix confirmed that all observed items loaded precisely onto their respective theoretical factors with loadings exceeding 0.50, establishing a clear three-factor structure (Hair et al., 2009).

Confirmatory Factor Analysis (CFA) was performed to validate the structural integrity of the tripartite model (EA, EB, and SC). The results indicated a superior model fit, with indices meeting or exceeding standard benchmarks: χ^2 = 342.79, df = 249 (χ^2/df = 1.38); GFI = 0.93; CFI = 0.98; and TLI = 0.97 (Hu & Bentler, 1999). The RMSEA was 0.03 with a PCLOSE of 1.00, reflecting minimal approximation error and an excellent fit between the theoretical model and the empirical data.

Standardised factor loadings ranged from 0.56 to 0.79, well above the 0.50 minimum, demonstrating strong convergent validity. Additionally, Composite Reliability (CR) values exceeded 0.70, and Average Variance Extracted (AVE) values were greater than 0.5 for all constructs (Fornell & Larcker, 1981). Discriminant validity was also confirmed, as the square root of the AVE for each construct was greater than its correlation with any other latent variable (Hu & Bentler, 1999). These psychometric evaluations confirm that the scale accurately measures SI according to the PISA 2025 framework and is highly suitable for experimental application.

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Procedures

The intervention was implemented over ten weeks, following the five-stage experiential STEM and IoT model. To mitigate potential confounding effects from variation in teaching approaches, the instructor for the experimental group implemented a structured protocol. Within this protocol, the instructor's role was confined to that of a technical facilitator and safety supervisor, deliberately moving away from a central, directive teaching role. Pedagogical interactions were designed to be technology-mediated. Students received direct feedback from IoT sensor data and system interfaces, shifting epistemic authority from the teacher to empirical evidence and reducing outcome dependency on individual teaching methods (Panergayo & Prudente, 2024).

Phase 1: Field exploration and problem identification

Students began with a field survey in Dieu Phong Hamlet. Through interviews with local farmers, they identified pressing agricultural issues, such as inconsistent irrigation schedules leading to water waste. This phase grounded the technical project in a real socio-scientific context, connecting science learning directly to community needs (Archer et al., 2015).

Phase 2: Scholarly inquiry and ideation

Students then researched electronics, sensor mechanics, and basic programming. In collaborative groups, they proposed technical solutions, sketching circuit diagrams and planning simple cloud-based control interfaces. This phase focused on translating academic theory into conceptual designs for engineering applications.

Phase 3: Engineering design and prototyping

In this hands-on phase, student groups assembled hardware, including microcontrollers, relays, and water pumps, and wrote the necessary code for IoT cloud integration. This practical work aimed to build SC and technical self-efficacy through direct experience.

Phase 4: Empirical implementation and data acquisition

This phase marked a key epistemic shift. Students deployed their prototypes in the field to collect real-time sensor data. Confronting messy, non-idealised data, like unpredictable soil moisture readings, forced them to navigate the inherent uncertainty of scientific experimentation, a process that challenges and refines EB (Allchin, 2012).

Phase 5: Critical reflection and iterative optimisation

In the final stage, students used the IoT-generated data to evaluate their system's performance, assessing factors like watering precision. They then iteratively refined their designs and reflected on the potential environmental impact of their solutions. These activities were designed to strengthen EA and systems thinking (Bandura, 2001; OECD, 2023).

Data Analysis

Data were collected at two distinct temporal points: Baseline (Pre-test – O1 and O3) and Endline (Post-test – O2 and O4). The primary measurement instrument was the standardised SI Scale. Throughout the 10-week experimental intervention, the research team rigorously monitored the experimental attrition rate to maintain group equilibrium and preserve the initial baseline equivalence between the experimental and control groups. To test the primary hypothesis regarding the efficacy of the IoT-integrated experiential STEM model (X), post-test data were analysed using Analysis of Covariance (ANCOVA), with pre-test scores serving as the covariate. This statistical approach was employed to neutralise any potential baseline discrepancies and isolate the net treatment effect. All quantitative analyses were performed using IBM SPSS Statistics version 26.0.

To supplement the quantitative findings and facilitate triangulation, qualitative data were gathered through two primary channels: (1) Student Learning Journals: Compiled throughout the 10-week intervention to capture real-time reflections and the evolution of students' engagement; (2) Retrospective Semi-structured Interviews: Conducted upon project completion with 12 purposively selected students. This subsample was identified through extreme case sampling, consisting of six students who exhibited the highest gain in SI scores and six who exhibited the lowest gain. These interviews aimed to elucidate the underlying psychological mechanisms and idiosyncratic experiences that facilitated or hindered the development of their SI.

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Ethical Considerations

This research adhered to the ethical principles of educational research and the Declaration of Helsinki. The University of Science and Education – The University of Da Nang's Institutional Review Board and Scientific Committee, alongside the administration of Ong Ich Khiem Secondary School, formally approved all research protocols and instruments.

As participants were minors (aged 16–17), informed consent was obtained through a two-tiered process. First, parents or guardians received a detailed information sheet outlining the study's goals, procedures, and potential risks, such as those related to electrical work during IoT assembly. Written parental consent was mandatory. Second, the study was explained to the students themselves, after which they provided written assent.

Participation was voluntary. Participants were clearly informed that their decision to join or withdraw would not affect their Physics grades, academic standing, or any school evaluations. To protect privacy, all personal data were anonymised using alphanumeric codes during analysis. Sensitive materials, including learning journals and interview audio, were stored in password-protected, AES-encrypted files accessible only to the core research team. Raw data will be securely disposed of one year after the completion of the final report, in accordance with institutional policies.

Given the hands-on nature of the IoT and agricultural activities, we conducted a dedicated safety training session before fieldwork in Hoa Nhon Commune. This session covered electrical safety for working with ESP8266 microcontrollers and water pumps, as well as hygiene practices for handling soil, ensuring all physical risks were managed.

Research Results

Quantitative Analysis of SI Dynamics

The study employed an NECGD. Prior to the intervention, preliminary analyses confirmed the baseline equivalence between the experimental group (n_E = 53) and the control group (n_C = 49) across critical foundational variables, including prior-semester Physics GPA, gender distribution, and baseline SI scores. This equivalence minimises selection bias and supports the use of ANCOVA to evaluate the intervention's effect (Dimitrov & Rumrill, 2003).

The ANCOVA employed pretest scores as covariates to adjust the posttest means, isolating the variance caused by the intervention. Table 7 shows both the observed and adjusted posttest means. The consistently higher adjusted means for the experimental group across all Science Identity measures suggest a positive change resulting from the IoT-STEM model.

Table 7
Descriptive Statistics and Adjusted Post-test Means for SI

Construct	Group	Pretest M (SD)	Posttest *M (SD)*	Adjusted Posttest *M*
SI	Control (nC = 49)	74.94 (2.33)	74.63 (2.39)	74.47
	Experimental (nE = 53)	74.64 (2.31)	76.80 (2.87)	76.65
SC	Control (nC = 49)	22.92 (0.84)	22.80 (0.84)	22.78
	Experimental (nE = 53)	22.89 (0.75)	23.22 (1.10)	23.19
EB	Control (nC = 49)	27.31 (0.85)	27.34 (0.91)	27.17
	Experimental (nE = 53)	27.08 (0.81)	27.76 (1.07)	27.73
EA	Control (nC = 49)	24.71 (0.87)	24.57 (1.23)	24.55
	Experimental (nE = 53)	24.68 (0.87)	25.24 (1.13)	25.20

Note: M = mean; *SD* = standard deviation. Adjusted means were estimated with pretest scores as a covariate; SI = Science Identity; SC = Science Capital; EB = Epistemic Beliefs; EA = Environmental Agency. Control group: n_C = 49; Experimental group: n_E = 53.

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The application of ANCOVA was methodologically appropriate given the study's pretest-posttest design. The unadjusted post-test means indicated a clear advantage for the experimental group ($M = 76.80$) over the control group ($M = 74.63$). After statistically adjusting for baseline pretest variance, the adjusted means (76.65 vs. 74.47) provided a refined estimate of the intervention's effect, confirming its significant positive impact on the dependent variable.

The results of the ANCOVA regarding the impact of the STEM-IoT model on overall SI are summarised in Table 8. The analysis revealed a highly significant difference between the experimental and control groups, $F(1, 100) = 17.46$, $p < .001$ (Field, 2024).

Table 8

ANCOVA Results for the Effect of IoT-STEM Intervention on Science Identity

Construct	*F*	*df*	*p*	η^2_p	Cohen'd
SI	17.46	1	< .001	0.15	0.82
SC	4.61	1	.03	0.04	0.43
EB	4.31	1	.04	0.04	0.42
EA	8.43	1	.005	0.08	0,57

Note: η^2_p= partial eta squared; ; Cohen's *d* = effect size of the intervention; SI = Science Identity ; SC = Science Capital; EB = Epistemic Beliefs; EA = Environmental Agency.

The overall SI score showed a large effect size (Cohen's $d = 0.82$), which, according to standard benchmarks in educational psychology, indicates a substantial impact (Aberson, 2019). This result supports the effectiveness of the experiential IoT-STEM model. The magnitude of the effect suggests that combining hands-on learning with real-time data technology may be more effective than conventional methods in moving students beyond knowledge acquisition toward seeing themselves as active participants in science.

Analysis of the three individual components revealed distinct patterns of growth. EA showed the strongest effect ($F = 8.43$, $p = .005$, $d = 0.57$). This medium-to-large effect suggests that applying physics and electronics to solve local agricultural problems, like optimising irrigation, meaningfully strengthened students› belief in their own capacity to enact environmental change.

Significant, though more moderate, gains were also observed for the other two components. SC increased ($F = 4.61$, $p = .030$, $d = 0.43$), reflecting the accumulation of practical IoT skills and technical confidence through hands-on engineering. For EB ($F = 4.31$, $p = .04$, $d = 0.42$), the effect likely stemmed from students' repeated engagement with unpredictable, real-time sensor data, which challenged their assumptions about certainty in science and emphasised the role of evidence.

The intervention's impact varied across the three Science Identity components. The strongest effect was on EA, aligning with the forward-looking goals of contemporary science literacy frameworks. This pronounced impact likely stems from the direct feedback loop of the IoT-agriculture context, where students could immediately observe how their technical actions, like adjusting a sensor threshold, led to tangible environmental outcomes.

The effects on SC and EB, while positive and statistically significant, were more moderate. These components may require longer or differently structured engagements to develop fully, yet their growth here indicates a foundational shift. These variations in effect size highlight a key outcome: the program most effectively fostered the actionable competence that turns scientific awareness into real-world participation.

Qualitative Analysis of SI Dynamics

Qualitative analysis of learning journals and retrospective interviews with 12 participants helped explain the quantitative gains in EA and EB. The data revealed that Science Identity did not develop in a simple, linear way. Instead, its formation involved a dialectical process, which this study terms epistemic friction. This friction occurred as students' existing assumptions encountered and grappled with the uncertain, complex realities of hands-on scientific work.

In contrast to the predictable experiments in textbooks, real-time data from IoT sensors in the field, such as soil moisture readings, were often noisy and inconsistent. This discrepancy did not lead to immediate understanding but instead generated frustration and doubt. One student's journal entry captured this reaction clearly:

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> *"Honestly, our group was so annoyed today. The sensor showed 85%, then suddenly 40%. We thought it was just broken. My teacher explained that real field data isn't always smooth. It's frustrating because I just wanted a simple, 'right' answer to finish the task."* (N.T.H., Group 3).

This frustration marks a critical point where the students' initial belief, that science yields single, precise answers, began to break down. To move forward, they had to shift from seeking a predetermined "right" answer to engaging with the data, questioning its variations, and interpreting what it might mean for their irrigation system.

To work with this uncertainty, students started using practical strategies like calculating averages to smooth out erratic sensor readings or comparing data trends over time. While technically focused, this work became a practical lesson in critical thinking. As one student noted:

> *"The graph looked all messy and chaotic; we almost deleted the erratic points to make it look nicer and easier to read. But then we recalled the lesson about error margins. If we hide them, it won't be real data anymore. Now I'm starting to really understand that doing science isn't always about getting a perfect, neat line; sometimes it means wrestling with messy, real-world data like this."* (P.V.M., Group 1).

This reflection marks a crucial shift in the students' learning journey. Moving beyond the mere acquisition of technical skills like programming or data processing, they began to adopt a more careful and evidence-oriented approach. Their decision to accept the inherent complexity of real data, rather than altering it for a cleaner appearance, demonstrates that their learning transcended simple rule-following. It indicates a developing maturity in scientific thought, as they started to appreciate the true nature of inquiry, a process that inherently embraces uncertainty and imperfection.

When students overcame the stage of epistemic friction and witnessed their IoT systems functioning effectively, their sense of technological mastery was transformed into a robust belief in their capacity to address socio-environmental crises. One student captured this moment of realisation:

> "*Whoa, when the pump kicked in all by itself, I literally screamed! Oh my god, it actually worked! I always thought saving the environment and fighting droughts was something only, like, real scientists in lab coats did. But here I am, using physics formulas from class to solve an actual, real-life problem. The feeling of building something useful with my own hands*." (H.M.T., Group 4).

This realisation emerged from directly engaging with the earlier difficulties. For H.M.T., the frustration with inconsistent data and the effort to interpret it became necessary steps. Working through those challenges made the eventual outcome ("it actually worked!") personally significant. The narrative traces a shift from viewing science as a distant activity done by experts to claiming personal agency: "here I am… solving an actual, real-life problem." This transition captures the development of EA, an identity built through overcoming authentic challenges, not through passive, teacher-centred learning.

Discussion

The IoT-integrated STEM model led to a substantial increase in overall Science Identity within the experimental group, with a large effect size *(d* = 0.82). This value surpasses common benchmarks for educational significance (Hattie, 2008) and is higher than the average effect reported for comparable STEM interventions (Cao X et al., 2025). The effectiveness of the model likely stems from its core synergy: combining the authentic Engineering Design Process with real-time data feedback from IoT sensors, which helps students transform abstract physics knowledge into a concrete sense of scientific agency. Furthermore, this success aligns with contemporary meta-analyses indicating that integrated, project-based STEM models can be particularly effective in Asian educational contexts, where structured technological integration complements established collaborative learning traditions (Zhang & Ma, 2023).

A granular analysis of SI components reveals that EA was the most profoundly impacted dimension, achieving a medium-to-large effect size (Cohen's *d* = 0.57). This finding is of paramount importance, as EA represents the central innovative thrust of the PISA 2025 Science Framework (White et al., 2023), reflecting the imperative to equip students with agency in the Anthropocene. The observed effect size (*d* = 0.57) is not only statistically significant

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but also educationally meaningful, indicating a substantial practical impact on students' sense of agency. The mechanism underlying this improvement can be attributed to the capacity of IoT technology to provide quantifiable and immediate feedback on the environmental efficacy of students' engineering solutions, such as optimised water resource management. Witnessing the direct ecological benefits of their technological artefacts bolstered students' self-efficacy, a prerequisite for sustained socio-ecological action mediated by connected technologies.

It is noteworthy that the intervention model produced a measurable effect (d = 0.43) on SC, a component often regarded as relatively "fixed" and closely tied to familial background. This success likely stems from the STEM-IoT approach, where the Engineering Design Process (EDP) and hands-on fabrication play a central role, enabling students to accumulate practical experience and digital skills. The findings align with evidence from design-based learning research, which indicates that EDP is an effective tool for fostering competencies such as scientific creativity (McClain CR, 2025; Kontkanen et al., 2025). More importantly, embedding the project within a local agricultural context provided students with a new form of STEM-related social capital. For students with fewer privileges, this could serve as a key to unlocking doors into the world of STEM, which has often remained inaccessible to them (Panergayo & Prudente, 2024).

Conversely, EB exhibited a marginal yet significant shift of d = 0.42. Although the most modest of the three components, this change is substantial considering that EB represents a deep-seated psychological construct resistant to short-term intervention. This growth is attributed to the requirement for students to interact with "non-idealised" and idiosyncratic data harvested by IoT sensors. Navigating "noisy" datasets forced students to confront the inherent uncertainty (tentativeness) of scientific knowledge, a departure from didactic consumption. This fostered epistemic maturity, particularly in terms of commitment to evidence and the acceptance of the evolving nature of science. While existing literature highlights the impact of data-driven assessment on achievement (d from 0.24 to 1.68) (Peters et al., 2021; Schiefer et al., 2022), this study extends the field by utilising student-generated environmental data as a catalyst for epistemic change, a critical predictor for future scientific literacy.

A key strength that enhances the practical value and sustainability of this research is its attention to fidelity of implementation, as framed by Century et al. (2010). By designing the STEM-IoT model around a clearly structured five-phase protocol, the study effectively isolates the impact of the pedagogical method from variables related to a teacher's individual skill or personal teaching style. In this model, the teacher's role was redefined as a technical and safety facilitator, while cognitive authority was shifted from the instructor to the empirical data stream generated by the IoT sensors. This mechanism allowed students to interact with and receive feedback directly from objective, empirical evidence, helping to standardise the learning experience and minimise implementation variance across different classroom contexts. Consequently, the significant gains observed in the components of SI, particularly EA, are not simply the result of unique, non-replicable teaching talents but a direct outcome of this systematic instructional design. This finding strongly supports the potential to effectively scale and transfer the IoT-STEM model to other secondary schools nationwide, even in settings where teachers may not yet be IoT experts but can successfully guide students using the standardised protocol.

Limitations and Future Research Directions

Despite its contributions, this study has several limitations that provide directions for future research. First, the convenience sample from a single secondary school, while adequate for establishing baseline equivalence, limits the generalizability of the findings. The results may reflect the unique context of this school and its students. To address this, future research should test the IoT-STEM model in multiple schools across diverse regions to determine whether its effects hold in different educational and socioeconomic settings.

Second, while the quasi-experimental design and the use of ANCOVA strengthen internal validity, they cannot fully eliminate threats such as differential history or maturation. Although the student-centred, technology-mediated design aimed to reduce direct teacher influence, the potential confounding effect of the teacher cannot be entirely ruled out. To better isolate the impact of the pedagogical model, future studies could employ cluster-randomised trials with a larger number of teachers, allowing for multi-level modelling to separate teacher effects from intervention effects.

Third, the study measured outcomes immediately after the 10-week intervention. Therefore, the long-term durability of the improvements in Science Identity remains unknown. It is unclear whether the shifts in self-perception, competence, and beliefs are sustained over time or whether they translate into longer-term STEM engagement or career choices. Longitudinal follow-up studies (e.g., 6–12 months post-intervention) are necessary to answer these critical questions about persistence and predictive validity.

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Finally, the successful implementation of such a technology-rich model hinges on teacher readiness. While this study structured the intervention to minimise variation in facilitation, widespread adoption would require systematic teacher support. Future implementation research should, therefore, investigate the role of targeted professional development in enabling teachers to effectively guide students within such complex, inquiry-driven learning environments.

Conclusions and Implications

This study demonstrates that integrating IoT technology into hands-on STEM activities within an agricultural context is an effective approach for developing secondary school students' SI. The intervention model achieved more than just teaching technical skills; it aimed to cultivate the key competencies outlined in the PISA 2025 framework, with a central focus on developing students' EA, SC, and more sophisticated EB. A core finding highlights the pivotal role of Epistemic Friction, the cognitive challenge that arises from interpreting noisy, real-world IoT data. This suggests an important principle for STEM education: instead of simplifying problems, educators should use digital tools to engage students with authentic, complex scenarios. It is through grappling with this uncertainty that students learn to reason, evaluate evidence, and act as autonomous scientific agents.

The Ministry of Education and Training should explore integrating noncognitive metrics such as social intelligence SI and adaptive ability EA into the national standardised assessment framework. This step is not merely about aligning with the comprehensive evaluation approach of PISA 2025, but more importantly, it addresses the practical needs of education in Vietnam: to foster individuals equipped with well-rounded qualities and skills for life and work. To ensure such a policy translates into real impact, a clear roadmap is essential, starting with pilot assessments, training teachers in evaluation methods, and designing school educational activities that genuinely cultivate these competencies in students.

Physics and Technology educators are encouraged to adopt interdisciplinary instructional designs that are deeply situated within local socio-environmental contexts (e.g., sustainable agriculture, climate change mitigation). The integration of digital data acquisition tools, specifically IoT sensors, is recommended to enhance empirical rigour in the classroom. This approach not only fosters scientific inquiry but also cultivates advanced data literacy and analytical competencies among secondary students.

There is a critical need for targeted Professional Development programs focusing on data-driven pedagogy and technological integration. Equipping teachers with the necessary Technological Pedagogical Content Knowledge is a vital prerequisite for the effective implementation of complex, inquiry-based models like the IoT-integrated STEM framework.

This research contributes a standardised psychometric instrument (the SI Scale) specifically validated for the Vietnamese educational landscape and proposes a highly feasible experimental model. These contributions provide a robust empirical foundation for the localisation of international educational standards, effectively bridging the gap between global benchmarks and domestic educational praxis.

Declaration of Interest

The authors declare no competing interest.

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Appendix

Science Identity scale

Instructions: Please read each statement carefully and indicate your level of agreement by selecting the option that most accurately reflects your perspective, according to the following 5-point Likert scale:
1: Strongly Disagree; 2: Disagree; 3: Neutral / Undecided; 4: Agree; 5: Strongly Agree

Item Code	Survey Items	1	2	3	4	5
EB	Component 1: Epistemic Beliefs					
EB1	Data derived from sensors is significantly more reliable than personal experiences or observations.					
EB2	I trust peer-reviewed scientific reports regarding agricultural issues more than information sourced from social media.					
EB3	When confronted with conflicting information about a technological solution, I seek explanations from multiple experts to reach a consensus.					
EB4	I understand that scientific data, even from IoT technology, always involves a certain degree of uncertainty.					
EB5	To make informed decisions on agricultural issues, I verify the qualifications and professional reputation of the experts providing advice.					
EB6	I understand that scientific knowledge and solutions are subject to change when superior data or newer research emerges.					
EB7	I consistently question the accuracy and reliability of sensor devices before drawing a conclusion.					
EB8	Scientific evidence serves as the primary basis for me to revise my perspectives or technical solutions.					
SC	Component 2: Science Capital					
SC1	I perceive myself as capable of utilising scientific knowledge and technology (e.g., in smart agriculture).					
SC2	I consider scientific concepts related to agriculture and the environment to be vital for my future career and life.					
SC3	I find it engaging to participate in hands-on activities and engineering design tasks (e.g., assembling IoT systems).					
SC4	My family and friends encourage me to pursue my interests in science and technology.					
SC5	I am acquainted with adults whose professions involve the application of scientific or technical expertise.					
SC6	I believe that I can achieve professional success by pursuing a career in STEM or technology.					

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Item Code	Survey Items	1	2	3	4	5
SC7	I typically achieve high academic performance in assignments or subjects related to Science and Technology.					
EA	Component 3: Environmental Agency					
EA1	I believe I am capable of applying scientific and IoT knowledge to mitigate local environmental challenges.					
EA2	I understand that individual actions can significantly influence complex socio-ecological systems.					
EA3	I intend to take proactive steps (e.g., community advocacy, sustainable consumption) to promote environmental solutions.					
EA4	I believe that science and technology can provide feasible solutions to address global environmental crises.					
EA5	When evaluating technology, I consistently consider its potential long-term impacts on the environment and social equity.					
EA6	I believe that my community or peer group can collaborate effectively to improve resource management.					
EA7	I am willing to maintain sustainable agricultural practices even if they require more effort or are less convenient.					
EA8	I recognise that human impact on Earth systems is a critical issue that necessitates evidence-based scientific solutions.					
EA9	I believe that IoT technology enables more effective resource monitoring and management than traditional methods.					

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